TESI DE MASTER UNIVERSITAT POMPEU FABRA

Dynamic Control System for Sonic Interaction Based on Human Physiology

by

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"People who think they know everything are a great annoyance to those of us who do."

- Isaac Asimov

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Abstract

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This projects aims at testing different sonification strategies for measuring to what extent the human auditory system can be used as primary interface channel for communicating, exploring, and interpreting physiological data, and its interactions in different contexts. Auditory display techniques and Sonic Interaction Design approaches (SID) are at the core of this project, in order to design a system capable of defining dynamic physiology-to-sound mappings, adapting to different purposes. In a musical context, we hypothesise that such approach will achieve better results than pre-define, ad hoc mappings in terms of perception, control and expressiveness.

Keywords: Sonification, Sonic Interaction Design, Physiology, Music, BCI, HCI.

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Chapter 1

Introduction

1.1 Summary

Research efforts in the field of cognitive neuroscience and physiological computing, make possible nowadays to extract meaningful and accurate mental state information from EEG brain activity[1][2]. Particularly, focusing on emotion psychological framework it is known that affective experiences are well characterised by two main dimensions: arousal and valence [3][4]. The dimension of valence ranges from highly positive to highly negative, whereas the dimension of arousal ranges from calming or soothing to exciting or agitating. This EEG data can be expressed via visual or sonic displays, as in the case of neurofeedback training paradigms[5]. In the musical domain, real time EEG data has also been used since 1965, when pioneers such as Alvin Lucier introduced it to the artistic domain, using audification of alpha waves for music composition[6].
Nevertheless, within the musical domain, the expressive capacities of human physiology as part of an interactive music system has never been explored in depth. In particular, the use of EEG has been rather specific in this domain, and the state of the art in this regard shows important limitations in terms of meaningful musical expression and control (low band-with, noisy signals, intrusive equipment, etc.)[7]. Artists such as Atau Tanaka and researchers from EAVI have pioneered this research line, but rather focusing in other types of bio-signals (EMG) [8][9].
Coinciding the current state of the art on physiological computing and computer music, we aim at exploring the potential of EEG for expressive music control in a music performance scenario.
In order to achieve this goal, we propose to estimate valence and arousal responses from players EEG activity in real time, and estimate a 2-dimension value within the valence-arousal space. Afterwards, this data will be mapped to some Reactable filters

and effects parameters via a bi-linear interpolation algorithm, i.e. associate emotive information from the performer to appropriate music control parameters. The direction of the mapping will be created ad hoc via associating 4 coordinates from valence-arousal state phase to 4 extreme 2 dimensional filters parameter values.
In contemplation of system usability evaluation, we will also implement a gain controller object that will allow players to calibrate till what extent the EEG-driven mapping influences the control of filters and effects. An experiment with Reactable expert users will be carried out in order to see if introduction of EEG-driven music control parameters will enhance music expressiveness and implicit control, showed by (i) players preference over conventional gestural control and (ii) a continuous use of the gain.

1.2 Problem Statement

The use of bio-signals and the works integrating together BCI and sound synthesis can be divided in two different approaches. The first one is the use of physiological data converted directly into sound in the so called process of sonification[10]. In the second approach, the musician tries to build a musical system that uses the physiological data for the control of the sound production[11]. The project that we are presenting uses this second approach.
Reviewing the state of the art, we can distinguish two different problematic points that have to be taken into consideration when using BCI in a musical domain. First one, regards the EEG signal acquisition.
Non-invasive BCI approaches, such as Emotiv[12] and Neurosky[13] are becoming common in these domain since they make use of low cost devices. Nevertheless, such devices are hard-coded and it is complicated to have access to its signal processing algorithms. Even more, they emit lower quantity signal than other higher-grade devices. Due to its wireless connections they can be more suited for a music performance scenario, yet possible user movements are more probable to process artifact signals and send them into the system[14]. Summing all up, we have decided to use a medical based EEG amplifier device named Mitsar[15] and instead of using pre-coded EEG feature extracted signal we have build a Matlab based classifier for our emotional feature analysis, based on current research on EEG [2][16].
The second problem arises, in the closing loop of the system, within the musical domain. In order to get an expressive musical output from the performance we need, apart from having reliable EEG signalling, non-trivial EEG to sound mappings. Best mappings may be achieved when there is a perceptual connection between performer actions and their effect on the musical output[14][17]. It has also been proven that using

self-customization mappings by the end users improves performance in a bio-feedback paradigm[18]. Therefore, we have implemented a brain mapping controller that will allow mapping preferences and adaptation by the performers. Moreover, we have based the mapping directions according to the musical into emotions research literature[19][20]. In addition, most of the research in musical instruments that make use of physiological signals lack from user evaluation studies on system music expressiveness. That makes difficult to test, analyse and contribute further on mapping design strategies and overall system properties. Therefore, we will evaluate our system musical expressiveness within a methodological framework [21].

1.3 Architecture

Our biological-controlled instrument will be mainly composed by three parts, as we can see in the figure below:

- EEG Acquisition
- Raw Data Processing
- Reactable Control

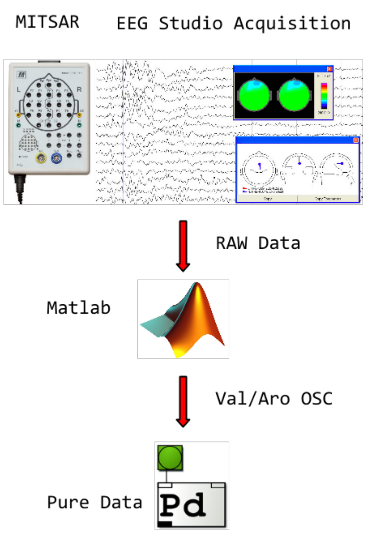

FIGURE 1.1: Systems Diagram

The first part of the system is composed by the EEG acquisition module. Mitsar EEG signal from the cap is amplified through the box and its raw signal is send to Matlab via a USB cable through EEGStudio software. This software that is used as a control

panel where you can set your cap montage, preprocesses raw data and filters it.
Later on, in the second part of the system, Matlab receives that data and the scripts calculates valance and arousal indexes after a calibration stage. Then, those V/A signals ranging from 1-9 are directly send via OSC with an Ethernet cable.
In the last stage, Pure Data receives OSC messages and uses them to control Reactable synth engine. Reactable objects, such as filters and effects are directly controlled with these OSC messages via a brain gain object. That brain gain object controls the final output of the system by interpolating tactile user parameters and valance-arousal ones received from Mitsar device.
The system generates log files in all of the 3 stages: EEGStudio Record, Matlab raw data and valance-arousal data, and PD logs from brain gain object that are saved in a textfile.

Chapter 2

Use of Physiology in Music

Neural oscillations or brainwaves are a form of bioelectricity, or electrical phenomena in animals or plants. A neural oscillation is rhythmic or repetitive neural activity in the central nervous system. Neural tissue can generate oscillatory activity in different ways, driven either by mechanisms within individual neurons or by interactions between neurons. In individual neurons domain, oscillations can appear as oscillations in membrane potential or as rhythmic patterns of action potentials, which then produce oscillatory activation of post-synaptic neurons. At the level of neural ensembles, synchronised activity of large numbers of neurons can give rise to macroscopic oscillations, which can be observed in the electroencephalogram (EEG).
EEG is described in terms of rhythmic activity and transients. The rhythmic activity is divided into bands by frequency. To some point, these frequency bands are a matter of nomenclature (i.e., any rhythmic activity between 8–12 Hz can be described as "alpha"), but these designations arose because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance.

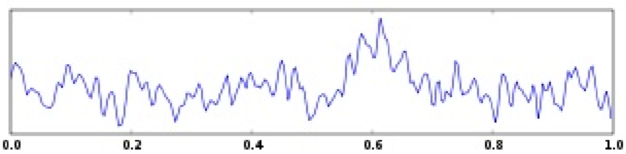

FIGURE 2.1: EEG Raw signal of one second

Human brainwaves were first measured in 1924 by Hans Berger. He termed these electrical measurements the electroencephalogram (EEG), which means literally 'brain electricity writing'. Berger first published his brainwave results in 1929 as "Uber das Elektrenkephalogramm des Menschen"[22]. The English translation did not appear until 1969. His results were verified by Adrian and Matthews in 1934 who also attempted to listen to the brainwave signals via an amplified speaker[23].

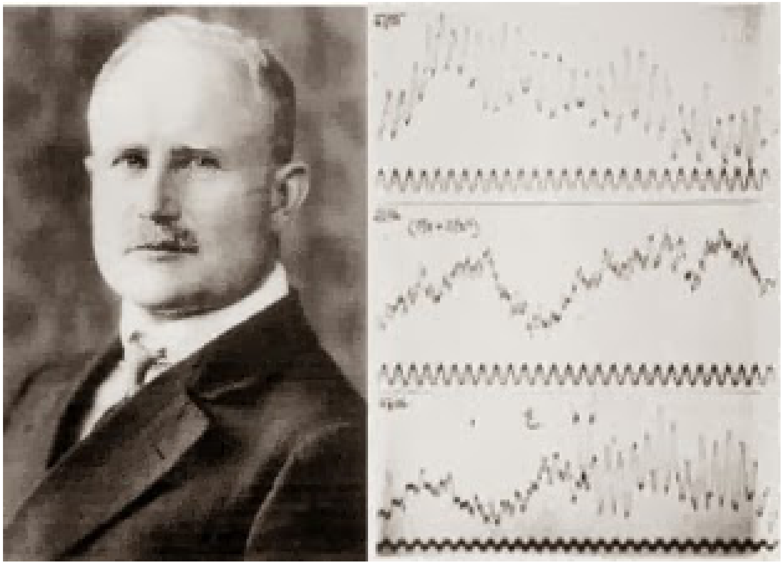

Figure 2.2: Hans Berger, first EEG plots

This was the first attempt to sonify human brainwaves for auditory display. The first instance of the intentional use of brainwaves to generate music did not occur until 1965, when Alvin Lucier[6], who had begun working with physicist Edmond Dewan, composed a piece of music using brainwaves as the sole generative source. Music for Solo Performer was presented, with encouragement from John Cage, at the Rose Art Museum of Brandeis University in 1965.

Figure 2.3: Music for Solo Performance, Alvin Lucier

In the late 1960s, Richard Teitelbaum was a member of the innovative Rome-based live electronic music group Musica Elettronica Viva (MEV). In performances of Spacecraft (1967) he used various biological signals including brain (EEG) and cardiac (ECG) signals as control sources for electronic synthesisers. Over the next few years, Teitelbaum

continued to use EEG and other biological signals in his compositions and experiments as triggers for the nascent Moog electronic synthesiser.

FIGURE 2.4: Musica Elettronica Viva (MEV)

Then, in the late 1960s, another composer, David Rosenboom, began to use EEG signals to generate music. In 1970-71 Rosenboom composed and performed Ecology of the Skin, in which ten live EEG performer-participants interactively generated immersive sonic/visual environments using custom-made electronic circuits. Around the same time, Rosenboom founded the Laboratory of Experimental Aesthetics at York University in Toronto, which encouraged pioneering collaborations between scientists and artists. For the better part of the 1970s, the laboratory undertook experimentation and research into the artistic possibilities of brainwaves and other biological signals in cybernetic biofeedback artistic systems. Many artists and musicians visited and worked at the facility during this time including John Cage, David Behrman, LaMonte Young, and Marian Zazeela. Some of the results of the work at this lab were published in the book “Biofeedback and the Arts”[24]. A more recent monograph by Rosenboom, “Extended Musical Interface with the Human Nervous System” [25], remains the definitive theoretical aesthetic document in this area.

In France, scientist Roger Lafosse was doing research into brainwave systems and proposed, along with musique concrete pioneer Pierre Henry, a sophisticated live performance system known as Corticalart (art from the cerebral cortex). In a series of free performances done in 1971, along with generated electronic sounds, one saw a television image of Henry in dark sunglasses with electrodes hanging from his head, projected so that the content of his brainwaves changed the colour of the image according to his brainwave patterns.

FIGURE 2.5: Rosenboom while performing

FIGURE 2.6: Vinil Cover of Corticalart

Starting in the early 1970s, Jacques Vidal, a computer science researcher at UCLA, simultaneously began working to develop the first direct brain-computer interface (BCI) system using a IBM mainframe computer and other custom data acquisition equipment. In 1973, he published "Toward Direct Brain-Computer Communication"[26] based on this work. In 1990 Jonathan Wolpaw et al [27] at Albany developed a system to allow a user to exercise rudimentary control over a computer cursor via the alpha band of their EEG spectrum. Around the same time, Christoph Guger and Gert Pfurtscheller also began researching and developing BCI systems along similar lines in Graz, Austria

In 2002, the principal BCI researchers in Albany and Graz published a comprehensive

Figure 2.7: Atau Tanaka in Biomuse

survey of the state of the art in BCI research, “Brain-computer interfaces for communication and control”. Then, in 2004, an issue dedicated to the broad sweep of current BCI research was published in IEEE Biomedical Transactions [28].
More recently, Brouse, Arsland and others [7] use EEG and EMG to control sound synthesis algorithms in order to build biologically driven musical instruments. A real time music synthesis environment and algorithms were developed to map these signals into sound. Finally, a "bio-orchestra", with two new digital musical instruments controlled by the EEGs and EMGs of two bio-musicians demonstrated this concept with a live concert on stage.

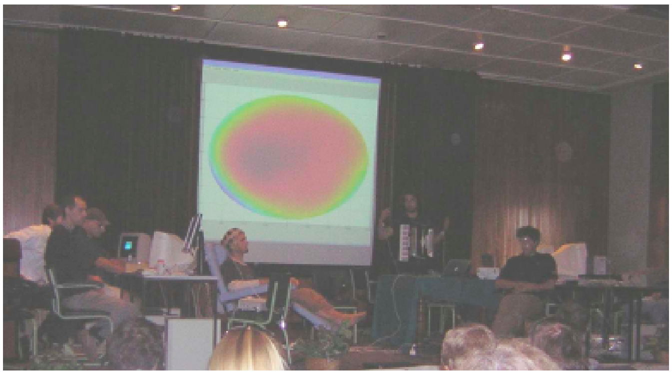

Figure 2.8: BioOrchestra from Arsland et al.

Chapter 3

System Description

In this chapter we will pursue a formal system description of our system. System Architecture is mainly divided in 2 modules, as we can see in figure below 3.1, EEG Module and Reactable Module. Firstly, we will explain how in the EEG Module we process raw data information and we categorise it into Valence and Arousal dimensions, and later on we will explain Reactable Module, where we process those Valence and Arousal in order to control music parameters.

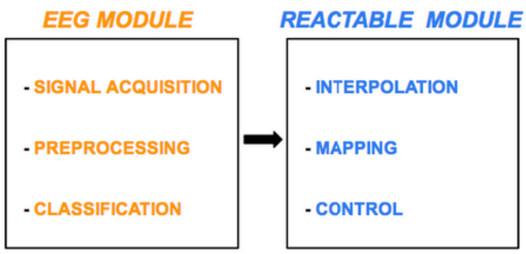

FIGURE 3.1: System Architecture Overview

3.1 EEG MODULE: EEG Processing into Valance-Arousal Dimensions

Figure above shows us a diagram that describes the EEG Module structure that we will discribe in this section. In that sense, firstly, we will give some context and foundations on EEG research, later on we will explain some of the research problems that arise working with affective states and physiological measures. Finally we will describe our EEG system architecture that will be divided into 3 main parts: signal acquisition, prepossessing and classification.

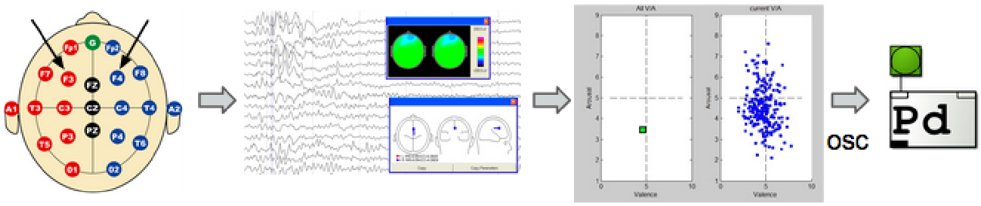

FIGURE 3.2: EEG Module Description

3.1.1 Context

Interactive music refers to a composition or improvisation in which software interprets live performance to produce music, which is generated or modified by computers. While arguably, not all the currently existing prototypes of devices for interactive music may present the same level of achievement or coherence, there are important reasons, perhaps often more intuited than stated, that turn live music performance and human computer interaction (HCI) in general, and musical instruments and tabletop tangible interfaces in particular, into promising and exiting fields of multidisciplinary research and experimentation. The reacTable, an ambitious tabletop musical instrument, is a good example of an instrument where musicians interact with computers, and it is a tool that facilitates the synergy between music and HCI. It is in fact, the design and use of computer-based tools for music composition and performance, which aims the development of diverse HCI's like the one proposed in this thesis.

The reacTable, it is played through specific objects that have different properties, such as generating raw sounds, playing samples, or manipulating qualities of the sounds played, with filters, adapting the sounds to specific keys, etc. The objects are handled in a very intuitive way in order to linearly change the settings of the computer generating the music. From the musical side, several computer music researchers have studied the control of sound in musical instruments as well as aspects of the communication between players and their instruments. A step further in this kind of communication, that may enhance the performance, would be not only "telling" the table directly what to do, but also including non-linear features, which aren't in the absolute control of the musician. Concerning this idea, the reacTable is a multimodal music instrument where the incorporation of new modalities such as based on biofeedback seems not only suitable but also exciting and useful from a musical point of view. This thesis focuses on the development of a new tool for music performance with reacTable, which will allow musicians to incorporate and map their emotional states of valence and arousal into the music.

3.1.2 Research Problem

Understanding how information is encoded in the brain is a problem that raises more questions than answers. Through brain imaging techniques such as electroencephalography now it is possible to detect which areas in the cortex are active when a subject is performing a given task, such as lifting their hand,etc. For an experienced observer, it is not difficult to infer the cortical correlate of the assigned task by looking into the EEG activation patterns for each channel of the EGG device. But while the activation for motor tasks is fairly standard, there are other conditions, which cannot be deduced with such ease, as deviation between subjects is greater. Those are, among others, the neural correlate of users' affective and emotional states, and the measure of their intensity in real time.
From a technical scope, affective Computing deals with processes that relates to, arises from, or deliberately influences emotion or other affective phenomena. The analysis and recognition of any kind of information given from any way of human emotional expression is a very profitable field that finds in the user's advertisement customisation its maximum exponent, reason why it is very diverse and advanced the techniques of this sort. Besides, the development of artificial intelligent algorithms that make machines "feel" even the ambiguity of human irony in a text, would be useful in terms of deciding whether a brain "feels" bored or just relaxed, if the task would consist just in understanding the cloud of features from EEG (or the implementation of a comprehension algorithm for relating the states of arousal/valence). Nevertheless it is not like that, again. Precisely because computing of this sort is popular, many projects are being developed to statistically analyse which parts of the brain are involved in specific emotional responses; there are many tools, theories and uncertainty, therefore it is often overwhelming to decide where to start testing.

3.1.3 Proposed Solution

Given the nature of the problem, the classification of the emotional states of Valence and Arousal of a musician playing the reacTable the solution proposed for the analysis of those emotional states will lie in the implementation of a machine learning algorithm, trained to give a highly accurate value for the arousal state (on a scale from 1 to 9 on the abscissa) and valence mood (on a scale from 1 to 9 on the ordinate). The training of the preliminary filter will follow the method described in the paper "DEAP: A Database for Emotion Analysis Using Physiological Signals" from Sander Koelstra et al., in which electrodes placed according to the international 10-20 system are studied, which are most relevant for analysing the emotional states from the rhythmic activity of theta,

alpha, beta and gamma bands - those most studied in association with arousal and valence. This correlation between cortical activity and emotion was possible due the exposure of 32 subjects to video clips, while music was rated in Last.fm in terms of level of valence, level of arousal, dominance and liking. That rating was recorded from the participants alongside EEG. All the data from both rating and the EEG database will be used in this thesis, as well as the statistical tools. After reproducing the results in the aforementioned paper, the validated tools will be used with new subjects, using their own ratings. So far, the machine learning tools proposed for classification will be based on, (in the first approach):

- Ordinal regression.
- Logistic regression.
- Pattern recognition.
- Neural Networks.
- Support Vector Machines.

3.1.4 Methods

All the algorithms will be implemented in Matlab, since all the code resources needed have a toolbox in this language. Following the paper above, the procedure will be:

For the features extraction:

- Filter the signal in the band $3 - 47$ Hz with Welch's method.
- Downsampling of the signal from 512 to 128 Hz.
- Eye blinks removal with a blind source separation technique in the EEGlab toolbox.
- Subtraction of the baseline power from signal.
- Filter the rhythmic bands theta (3-7) Hz, alpha (8-13) Hz, beta (14-29) Hz, and gamma (30-47) Hz.
- Correlation between power of rhythmic activity frequency bands and ratings due the Spearman's correlation coefficients.
- P-values obtained from the coefficients that will correlate direction (valence/arousal 1 to 9 rating), frequency band and electrode will merge into one p-value via Fischer's method.

For the classification:

- The Fischer's linear discriminant J selects relevant features.
- A naive Bayes statistical classifier for independence assumptions, that has been proven to work well with unbalanced classes, will discriminate which features belong to which classes (1 to 9, valence/arousal).
- In the article the F1-core for binary classifiers is employed in order to give relevant information of classes and the balance. So, for each participant, there will be a score that will evaluate their performance of emotion classification.

3.1.5 Overall EEG Module Description

In this part, we present an overall technical resume of EEG Module functioning.

1. Signal Adquisition: Mitsar Amplifier
   - 10-20 International Electrode Placement System.
   - F3 and F4 channels.
   - A1, A2 lobe channels as reference.
   - CZ ground electrode.
2. DSP: EEGStudio Software
   - Filtering (Low, High, Noch).
   - Downsampling to 128 Hz.
   - Rhytmic Filter (alpha, beta).
3. Valence/Arousal Classification: Matlab
   - Power Spectra in frequency domain (FFT).
   - Valance: beta f3 + beta f4 / alpha f3 + alpha f4
   - Arousal: alpha f4 / beta f4 + alpha f3 / beta f3

3.2 REACTABLE MODULE: From Affective States to Musical Parameters

In this section, we will explain our two main approaches used in order to build up a system capable of transposing affective states into a musical output. First system, will

be based on a global controller for some of the Reactable objects, while the second one will be based on a low-frequency oscillator that will act in a local manner.

3.2.1 Theoretical Framework

Music has been widely accepted as one of the languages of emotions. The possibility to select appropriate affective music can be helpful to adapt music to our emotional interest. Nevertheless, only recently scientists have tried to quantify and explain how music influences our emotional states. According to Scherer (1984), emotions may be conceived as consisting of various components: cognitive appraisal, physiological activation, motor expression, behaviour intentions, and subjective feeling. Emotional states can be described as particular configurations of these components.For a long time, cognitive sciences have been studying the foundations of emotions. More recently, computational models have also been proposed and are being applied in several domains (e.g. music, dance, and cinema). There are distinct approaches and techniques used to generate music with appropriate affective content. Starting from results of previous work (Schubert 1999), Livingstone and Brown [29] established relations between music features and emotions. Both emotions and a set of music emotion structural rules were represented in a 2-Dimensional Emotion Space with an octal form.

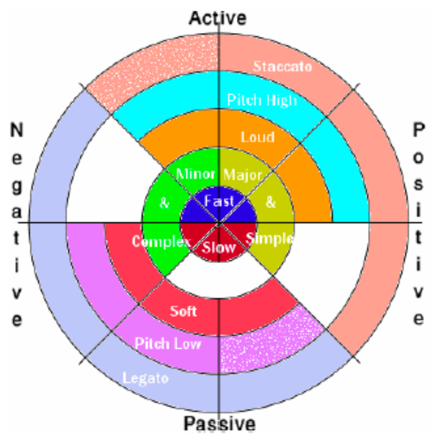

FIGURE 3.3: Primary V/A music categories

For our approach into musical emotions we will follow that approach that combines categorical and dimensional approaches to emotion expression to illustrate that the code allows performers to communicate both graded signals (level of activity) and categorical signals (happiness). Each emotional expression is placed at an approximate point in a two dimensional emotion space constituted by valance and activity level [3].

3.2.2 Reactable BCI System - Global Control

Reactable main parameter of filters and effects, accessed by rotation of the object, and second parameter, controlled with finger movement around the object, will be controlled by EEG V/A features through a bi-linear interpolation.
In mathematics, bilinear interpolation is an extension of linear interpolation for interpolating functions of two variables (e.g., x and y) on a regular 2D grid.

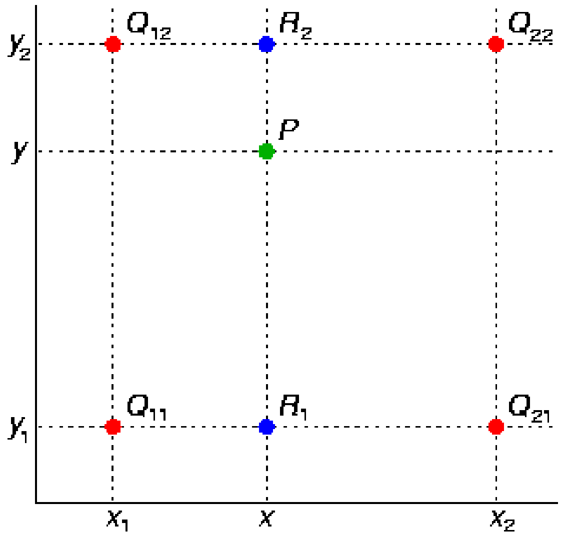

FIGURE 3.4: 2D grid for linear interpolation

Mathematically, the desired interpolation point is calculated as this:

$$
\begin{aligned}
f(x,y) \approx\; & \frac{f(Q_{11})}{(x_2-x_1)(y_2-y_1)}(x_2-x)(y_2-y)+ \\
& \frac{f(Q_{21})}{(x_2-x_1)(y_2-y_1)}(x-x_1)(y_2-y)+ \\
& \frac{f(Q_{12})}{(x_2-x_1)(y_2-y_1)}(x_2-x)(y-y_1)+ \\
& \frac{f(Q_{22})}{(x_2-x_1)(y_2-y_1)}(x-x_1)(y-y_1) \\
=\; & \frac{1}{(x_2-x_1)(y_2-y_1)}\Big(f(Q_{11})(x_2-x)(y_2-y)+ \\
& \qquad f(Q_{21})(x-x_1)(y_2-y)+ \\
& \qquad f(Q_{12})(x_2-x)(y-y_1)+ \\
& \qquad f(Q_{22})(x-x_1)(y-y_1)\Big)
\end{aligned}
$$

Our system implemented in PD, figures above, sends Arousal and Valance values received from Matlab to two distinct interpolators that control in a loop both musical parameters from Reactable objects. Brain gain object controls the overall values, in a second interpolation stage, send to object parameter by matching tangible user parameters and the ones received from BCI.

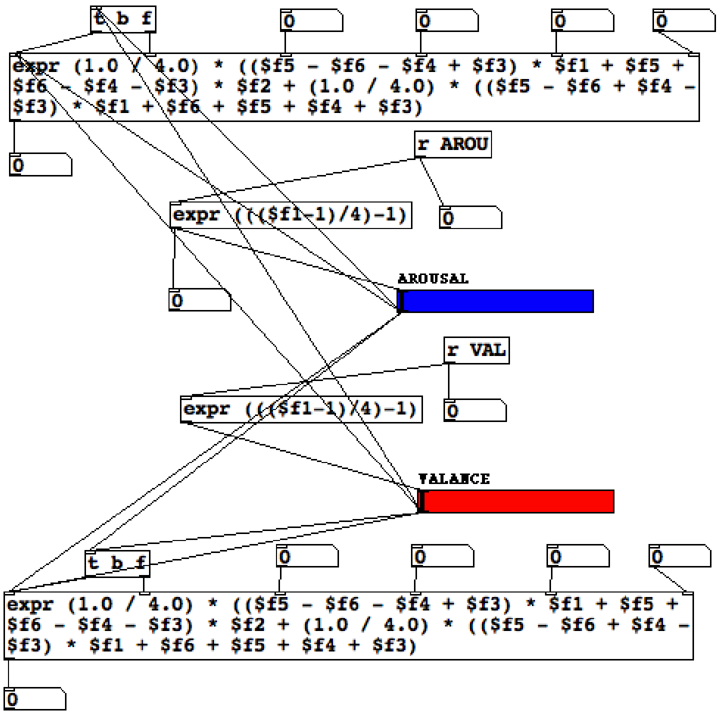

FIGURE 3.5: PD interpoler

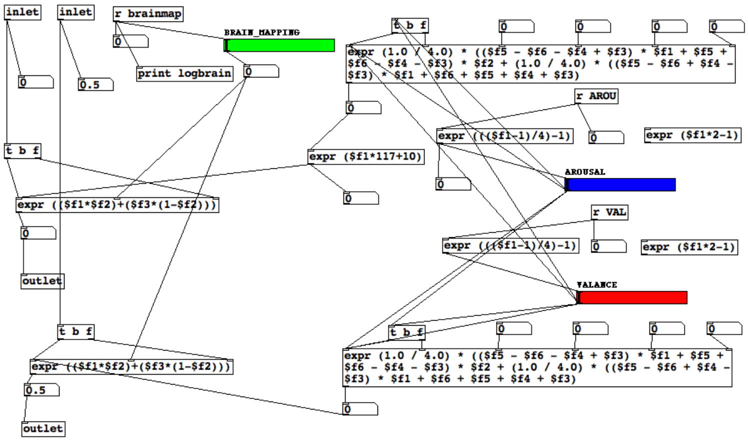

FIGURE 3.6: Overall PD interpoler with Brain Gain object

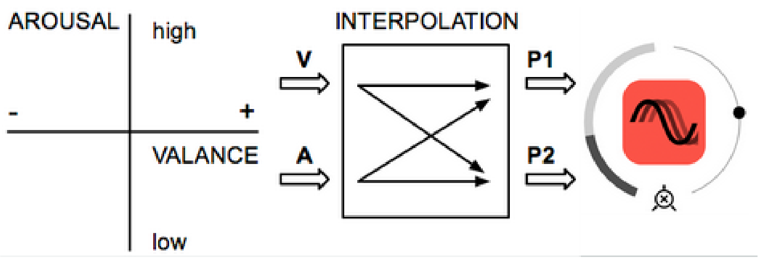

FIGURE 3.7: Interpolation Schema

Above we can see an example diagram of the brain object controlling a filter, and also the same architecture implemented in PD. When the brain gain object is at maximum value the object parameters are totally controlled by EEG features. In the case when brain object is at zero, the object parameters can only be controlled by tactile movements from the user. In other cases, the final parameter values are the result of an interpolation between tactile settings and BCI features.

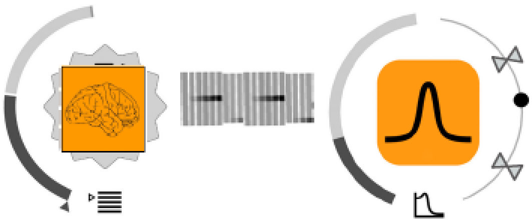

FIGURE 3.8: Brain object controlling a Filter

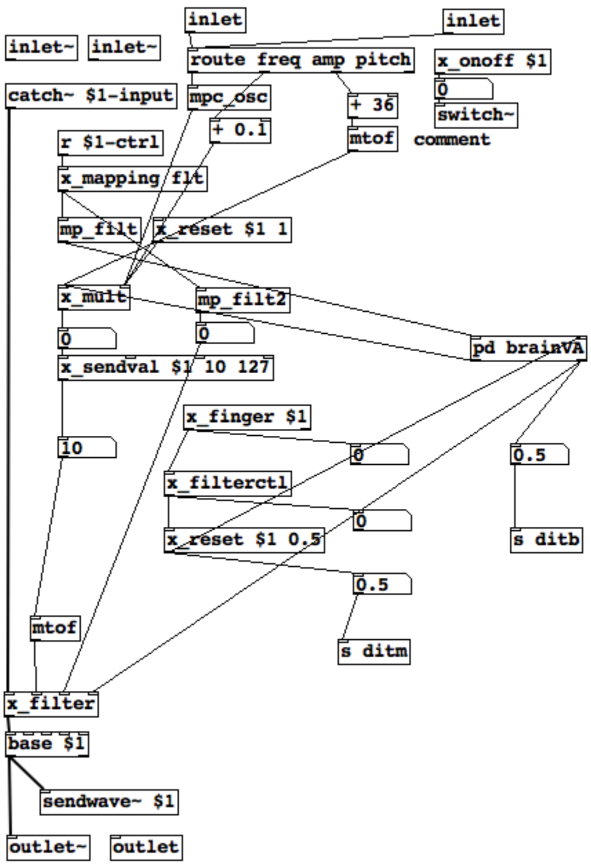

FIGURE 3.9: PD filter architecture

3.2.2.1 Mapping on Reactable Objects

The objects that will be controlled are a filter, a delay, a distorter and a modulator. The brain gain object will act globally, effecting all the objects mentioned above placed in the table during performance. The mappings are made accordingly to music timbre characteristics. The four extreme values for the Reactable system in the interpolation mapping are indicated below:

- Filter:
  - Valance-Arousal (-1,-1) to CuttOff-Resonance (10,0)
  - Valance-Arousal (-1,1) to CuttOff-Resonance (10,1)
  - Valance-Arousal (1,-1) to CuttOff-Resonance (127,0)
  - Valance-Arousal (1,1) to CuttOff-Resonance (127,1)
- Delay:
  - Valance-Arousal (-1,-1) to Delay Time-Feedback Amount (0,0)
  - Valance-Arousal (-1,1) to Delay Time-Feedback Amount (0,1)
  - Valance-Arousal (1,-1) to Delay Time-Feedback Amount (8,0)
  - Valance-Arousal (1,1) to Delay Time-Feedback Amount (8,1)
- Distortion:
  - Valance-Arousal (-1,-1) to Main Parameter-Dry/Wet (0,0)
  - Valance-Arousal (-1,1) to Main Parameter-Dry/Wet (0,1)
  - Valance-Arousal (1,-1) Main Parameter-Dry/Wet (4,0)
  - Valance-Arousal (1,1) to Main Parameter-Dry/Wet (4,1)
- Modulator/Chorus:
  - Valance-Arousal (-1,-1) to Main Parameter-Dry/Wet (0,0)
  - Valance-Arousal (-1,1) to Main Parameter-Dry/Wet (0,1)
  - Valance-Arousal (1,-1) Main Parameter-Dry/Wet (10,0)
  - Valance-Arousal (1,1) to Main Parameter-Dry/Wet (10,1)

Other effects such as granulator and ring modulator will be implemented for the Reactable BCI system

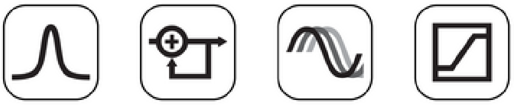

FIGURE 3.10: Reactable Effects and Filter

3.2.3 Reactable BCI System - Local Control

This local system, like global one, also allows players to calibrate till what extent the EEG-driven mapping influences the objects. Nevertheless, the way this influence is adjusted is achieved via an amplitude parameter, i.e. the distance of the lfo brain object to the controlled Reactable object. In that sense, when the local brain object is near the Reactable object the amount of BCI signal will be maximum. On the contrary, when the distance of the brain lfo to the Reactable object is augmented, the influence of BCI signal decreases.

Local system acts reassembling an lfo. In that sense, brain local objects controls a delta increase or decrease over central values set-up by user preferences. The amount of delta increase-decrease as we mentioned above, is controlled by the distance of the brain local gain to the object. In addition, finger parameter of the local controller can be manipulated in order to change sample and hold parameter values. This quantisation feature allows to send range of values in a discrete or in a continuum manner. Moreover, lfo brain object allows BCI signals to be triggered according to overall Reactable tempo. In that sense all BCI changes are triggered taking into account musical dynamics in performance.

Figure above, shows PD patch for the local brain object. We can observed that BCI signal output from pd VA interpolation box is later processed with a line object with a time frame of 1s and is later input to a an audio signal object.

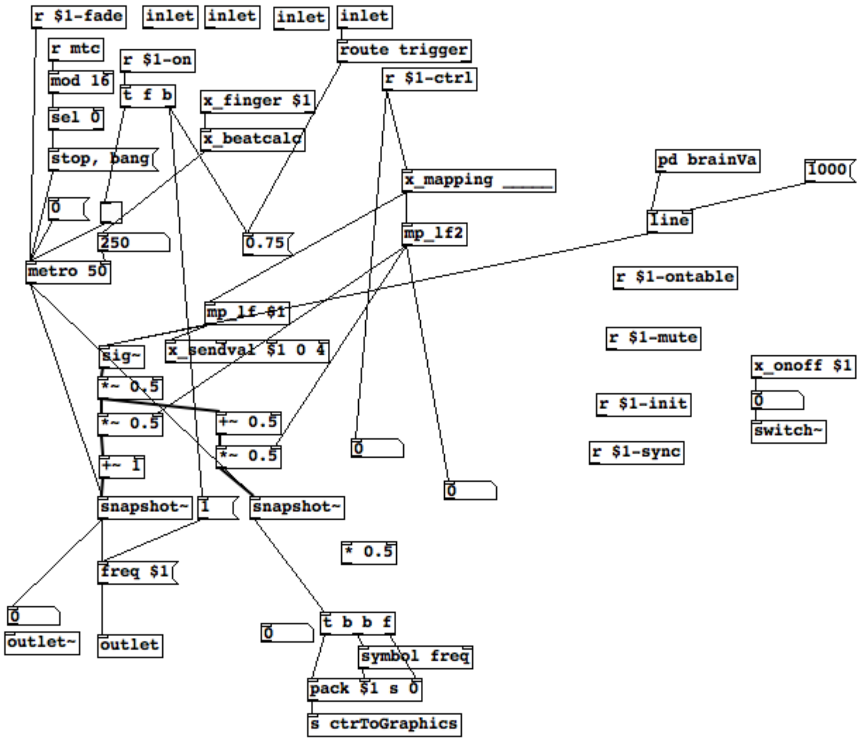

Figure 3.11: BCI Reactable Local Brain Gain Object

Chapter 4

Experimental Design

In this chapter, we will be presenting the overall experimental design carried out in order to test 2 different hypothesis:

- **H1**: There will be an augment in music expressiveness incorporating physiology-driven music control into Reactable.
- **H2**: There will be a neuro-feedback effect when using physiology-driven music control into reactable.

4.1 Experiment Description

Our main research hypothesis (H1) states that it is possible to integrate EEG brain signal using affective valence arousal descriptors in order to control music in expressive ways. Particularly, we will focus our musical framework within the Reactable table-top tangible interface, using some of its effects and filters parameters augmented via a "brain" object. That object will be implemented in two different ways and will manage the amount of mapping that it is send to the filters and effects . In Condition 1, we will be using a Global Brain Object and for Condition 2, the Local Brain Object. In contemplation of the evaluation of our hypothesis we propose to develop two different experimental conditions for one target group of Reactable Expert Users.

- Sample: 5 Reactable Expert Users.
- Repeated Measures.
- 2 Conditions:

  - C1 - Global Control
  - C2 - Local Control

- 2 Music Composition Tasks
  - T1- Positive Valence (Happy) and High Arousal (Active).
  - T2- Negative Valence (Sad) and Low Arousal (Calm).
- Duration: 1 h.
- Counterbalanced conditions and tasks.
- Previous system training session before 1st task.

Two subjective music composition tasks will be performed by five different users in two different sessions in each condition. They will have the availability of the full set of generators, effects and filters, controllers and global controllers from Reactable plus the "brain" controller object. Whereas users will have the restriction to perform with "brain" object on the table, they will have the possibility to move its gain from 0 to 1, meaning null variation from user defined parameters to full brain mapping control. That object functionality will be masked to users to prevent conditioning them. Once music performance is finished, a subjective and objective user experience evaluation method will be used. Firstly, an analysis of the observation of the users will be carried out together with an interview and a questionnaire. Secondly, we will analyse the gain of the log file from the "brain" object together with the user EEG recorded feedback. Last session, will serves us to control the differences between initial tasks and final tasks.

4.2 Experiment Protocol

The experiment lasts about 1 hour according the following protocol:

1. Information and consent form: The participant is explained each stage of the experiment, and the relation between brain activity and Reactable sound mapping; the consent form is signed (3 minutes).
2. Sensor placement and baseline state recording: The participant is sat in front Reactable, and the Mitsar is mounted. Impedance check ¡ 5 kOm. Blinking, closing eyes - checking that recording is ok. The baseline EEG activity is recorded for 2 minutes - eyes open, no motion. (10 minutes). File record.

3. Exploratory Phase: the experiment coordinator explains how the system works.
4. Experiment coordinator performs a live demonstration of how the system works
5. Once the explanation is done, the participant has 5 minutes to use the system, check the available sounds and make any question to the supervisor. The supervisor will assist the participant during the exploration phase (8 minutes).
6. (SAM1) Pre-test emotional state self-assessment: The participant fills two SAM scales (Subjective measures of emotional valence and arousal collected in paper through a 9-point Self-Assessment Manikin (Bradley and Lang, 1994))
7. Relaxation induction and calibration: The participant is asked to sit down in a chair and try to relax while listens a sound of waves during 2 minutes. EEG activity is recorded (2 minutes). File record.
8. (SAM2) Pre-test emotional state self-assessment (2 minutes).
9. (Impedance check before!) Task 1: The participant is asked to perform a musical task, either a exciting-happy or a relaxing-sad composition. The order of tasks will be randomised (10 minutes). File record.
10. (SAM3) Post-task 1 emotional state self-assessment (2 minutes)
11. Music Meaningfulness questionnaire (3 minutes)
12. Sensor removal (3 minutes)
13. Music Meaningfulness questionnaire against Reactable (3 minutes)
14. Interview (5 minutes) (only in the second session).
15. Debriefing

4.3 Experiment Explanation

In this section we can find the experiment description for Reactable expert user participants:
In this experiment we will assess the role of physiology-based interaction in music performance. We use EEG activity to estimate users' affective responses that later will be sent to a tabletop interface (Reactable) for controlling music parameters. For measuring EEG activity we use wet electrodes placed in the scalp. The experiment is composed of two sessions of 1 hour, to take place in different days. During the experiment you will be asked to perform two musical tasks using the Reactable. During the experiment we will

collect subjective measures regarding demography, music knowledge, music expressiveness, musicality, control and affective states. In the same manner, we will also collect performance and physiological data, together with video recordings. All the information will remain anonymous and will be used exclusively for analysis purposes. At the end of the second session we will also carry on interviews to gather feedback through open ended questions.

4.4 Music Meaningfulness Questionnaire

Here we show the likert scale questionnaires used to test music meaningfulness.
The System's properties are measured according to 3 variables:

- Mapping richness. Statement: I have found the control mapping rich and interesting".
- Synthesis richness. Statement: I have found the sound synthesis rich and interesting".
- Potential. Statement: The system shows great potential as a DMI".

Performance's aspects, on the other hand, were assessed through the following variables:

- Musicality. Statement: I have found the performance musical".
- Expressiveness. Statement: I have found the performance expressive".
- Virtuosity. Statement: The performers were able to control the instrument as real virtuosi".

4.5 Experimental Data: Measures and Statistical Analysis

From EEG module, we will get raw data from Matlab for the baseline. That recording will be compared with two tasks recordings, in order to see if the whole EEG acquisition systems is working under correct circumstances. Recordings from V/A indexes from Matlab will then be compared to SAM scales obtain by user ratings in each protocol steps.
Text files containing the use of brain gain button will be analysed together with music meaningfulness questionnaires and subjective measures extracted from video recordings. That will compose the overall data in Reactable module.

Finally, a comparison between EEG module measures and Reactable module measures will be performed to get finally results that will reinforce or not our research hypothesis. Next, we present a list of data measures that will be acquired during all experimental procedures.

- Main Research Hypothesis: *" It is possible to integrate EEG brain signal using affective valence arousal descriptors in order to control music in expressive ways"*
- Main 0-Hypothesis: *" It is* ***not*** *possible to integrate EEG brain signal using affective valence arousal descriptors in order to control music in expressive ways"*
- Secondary Research Hypothesis: *" There will be a neurofeedback effect when using physiology-driven music control into reactable."*
- Secondary 0-Hypothesis: *" There will* ***not*** *be a neurofeedback effect when using physiology-driven music control into reactable."*

Measures:

1. Affective Responses Part
    - Raw EEG data
    - V/A indexes
    - SAM scale questionnaires
2. Expressiveness Part
    - Music Meaningfulness Questionnaires
    - Brain Gain log file
    - Open Interviews

Statistical Analysis:

- Statistical Assumptions (Statistical Independence, Distribution).
- Test Statistic T.
- Distribution of 0-Hypothesis.
- α Significance Level.
- Pearson Correlation Analysis.

Chapter 5

Results

This chapter shows the analysis of the results obtained after carrying a total of 10 experiments with 5 subjects under 2 conditions. For each measure, affective and expressive, we present results both from condition 1 (global) and condition 2 (local).

5.1 Affective Responses Results

5.1.1 Condition 1

In the figure above 5.1 we can see the mean valence and arousal values, (ranging from 1 to 9) with their standard deviation error bars, of 5 subjects under 3 tasks. Task 0 represent the baseline recording while hearing during 2 minutes a relaxing sound of sea waves. Task 1 represents first high valence and high arousal music composition. Task 2 represents low valence and low arousal music composition.

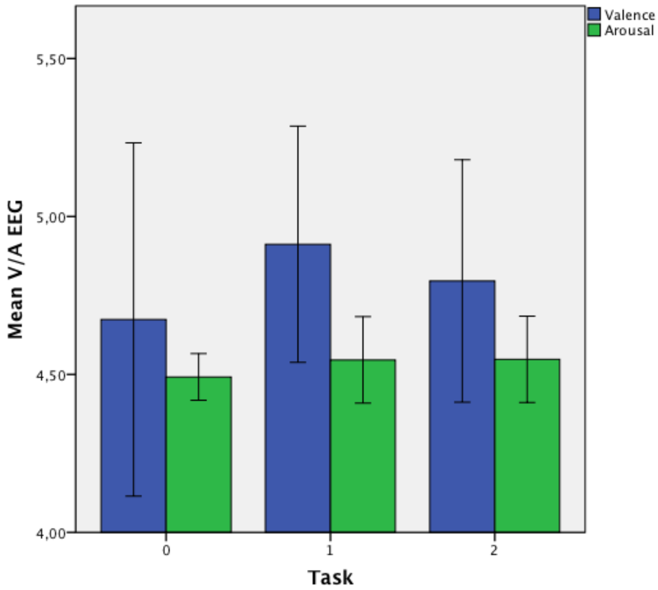

FIGURE 5.1: Mean Valence and Arousal Values from EEG Classification - Cond.1

Taking a look in to the graphic 5.1, we can see a slight variation between tasks in the expected direction. Nevertheless, it is not significant so far (valence $p = 0,28$) (arousal $p = 0,612$).

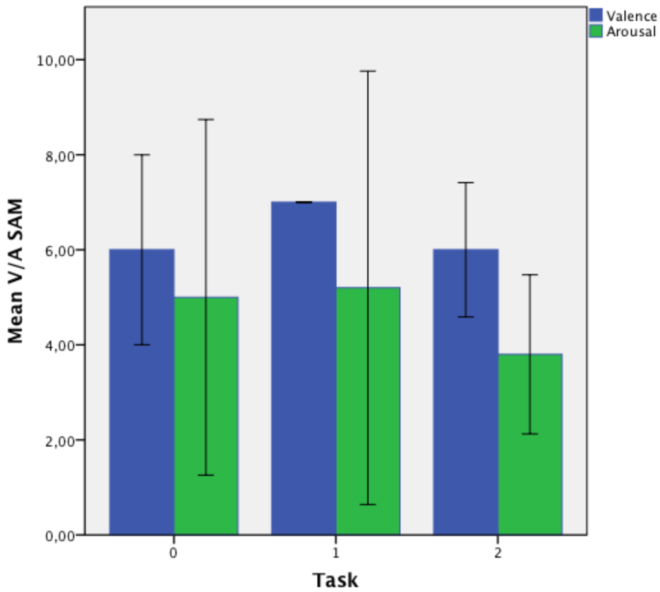

FIGURE 5.2: Mean Valence and Arousal Values from SAM scales - Cond.1

From SAM valence and arousal scales 5.2, we can see close to significant variations between task 1 and task 2 (valence $p = 0,071$) (arousal $p = 0,083$).

ANOVA

		Suma de cuadrados	gl	Media cuadrática	F	Sig.
Valence	Entre grupos	,142	2	,071	1,417	,280
	Dentro de grupos	,600	12	,050		
	Total	,741	14			
Arousal	Entre grupos	,020	2	,010	,512	,612
	Dentro de grupos	,238	12	,020		
	Total	,259	14			
SAMv	Entre grupos	3,333	2	1,667	3,333	,071
	Dentro de grupos	6,000	12	,500		
	Total	9,333	14			
SAMa	Entre grupos	5,733	2	2,867	,915	,083
	Dentro de grupos	37,600	12	3,133		
	Total	43,333	14			

FIGURE 5.3: ANOVA analysis between tasks of EEG and SAM indexes - Cond.1

5.1.2 Condition 2

In figures below 5.4, 5.5, we show the affective responses measures for sample group of 5 subjects within condition 2. In this case, Task 0 also represents the baseline recording. Yet, after counterbalancing between conditions, Task 2 represents high valence and high arousal music composition and Task 1 represents low valence and low arousal music composition.

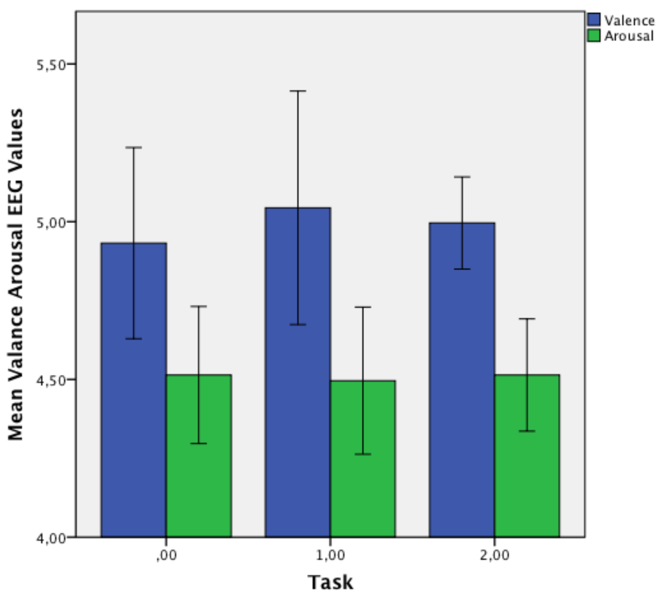

FIGURE 5.4: Mean Valence and Arousal Values from EEG Classification - Cond.2

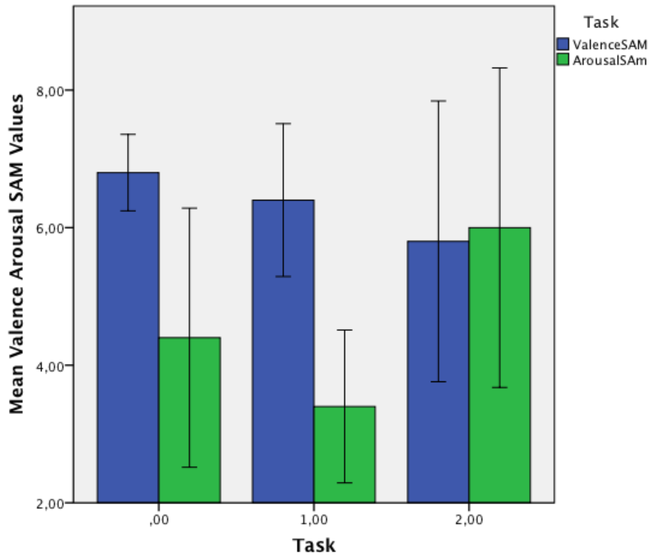

FIGURE 5.5: Mean Valence and Arousal Values from SAM scales - Cond.2

Tables 5.6, 5.7 below shows descriptive statistics analysis both from EEG and SAM measures and ANOVA analysis.

Descriptivos

		N	Media	Desviación estándar	Error estándar	95% del intervalo de confianza para la media: Límite inferior	95% del intervalo de confianza para la media: Límite superior	Mínimo	Máximo
ValenceEEG	,00	5	4,9320	,15156	,06778	4,7438	5,1202	4,76	5,13
	1,00	5	5,0440	,18501	,08274	4,8143	5,2737	4,76	5,27
	2,00	5	4,9960	,07301	,03265	4,9054	5,0866	4,88	5,08
	Total	15	4,9907	,14185	,03663	4,9121	5,0692	4,76	5,27
ArousalEEG	,00	5	4,5140	,10877	,04864	4,3789	4,6491	4,36	4,61
	1,00	5	4,4960	,11653	,05212	4,3513	4,6407	4,36	4,67
	2,00	5	4,5140	,08905	,03982	4,4034	4,6246	4,39	4,59
	Total	15	4,5080	,09799	,02530	4,4537	4,5623	4,36	4,67
ValenceSAM	,00	5	6,8000	,44721	,20000	6,2447	7,3553	6,00	7,00
	1,00	5	6,4000	,89443	,40000	5,2894	7,5106	5,00	7,00
	2,00	5	5,8000	1,64317	,73485	3,7597	7,8403	4,00	8,00
	Total	15	6,3333	1,11270	,28730	5,7171	6,9495	4,00	8,00
ArousalSAm	,00	5	4,4000	1,51658	,67823	2,5169	6,2831	3,00	6,00
	1,00	5	3,4000	,89443	,40000	2,2894	4,5106	3,00	5,00
	2,00	5	6,0000	1,87083	,83666	3,6771	8,3229	4,00	8,00
	Total	15	4,6000	1,76473	,45565	3,6227	5,5773	3,00	8,00

FIGURE 5.6: Descriptive Statistics of EEG and SAM scales - Cond.2

ANOVA

		Suma de cuadrados	gl	Media cuadrática	F	Sig.
ValenceEEG	Entre grupos	,032	2	,016	,757	,490
	Dentro de grupos	,250	12	,021		
	Total	,282	14			
ArousalEEG	Entre grupos	,001	2	,001	,049	,953
	Dentro de grupos	,133	12	,011		
	Total	,134	14			
ValenceSAM	Entre grupos	2,533	2	1,267	1,027	,388
	Dentro de grupos	14,800	12	1,233		
	Total	17,333	14			
ArousalSAm	Entre grupos	17,200	2	8,600	3,909	,049
	Dentro de grupos	26,400	12	2,200		
	Total	43,600	14			

FIGURE 5.7: ANOVA analysis between tasks of EEG and SAM indexes - Cond.2

By inspecting the data presented above, we can observe similar trends between EEG values and those from the SAM scales. Both arousal values show an increase between tasks in the expected direction, with a significance variation for the arousal SAM scale rating ($p = 0.049$). Tough, valence does not move into the expected direction, i.e. an increase in valence between task 1 that was low and task 2 that was high. In that sense, both valance affective responses measures decrease between tasks. Nevertheless, we do not find any significant differences for this last cases.

5.2 Expressiveness Results

5.2.1 Condition 1

Within expressiveness evaluation part, we can see that the mean value of the Brain Gain slight decreases between task 1 $(0,71)$ and task 2 $(0,64)$, nonetheless, we find no significance in these results ($p = 0,553$) 5.8. We can also see and increase valuation in System and Performance aspects that are close to significant 5.9. In system case we find a nearly to significant value ($p = 0,067$), yet in performance we see no significance ($p = 0,471$). Furthermore, we can observe a negative correlation between Brain Gain and System aspects, where we find a significant Pearson correlation ($rho = -0,783$, $\sigma = 0,007$).

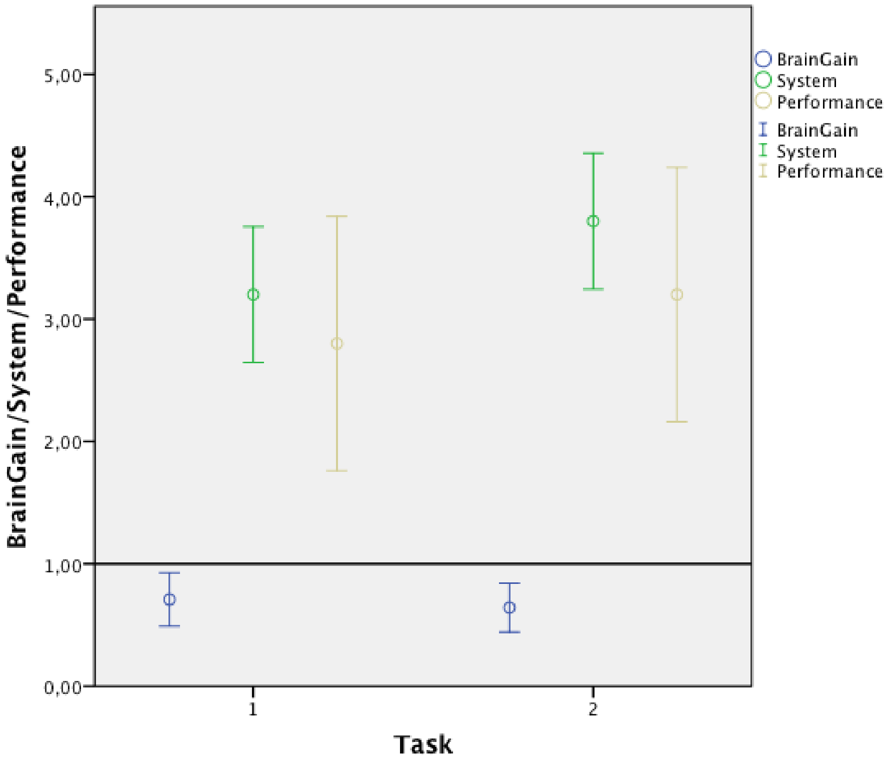

FIGURE 5.8: Mean Use of brain Gain and Likert Scale Ratings - Cond.1

ANOVA

		Suma de cuadrados	gl	Media cuadrática	F	Sig.
BrainGain	Entre grupos	,011	1	,011	,384	,553
	Dentro de grupos	,227	8	,028		
	Total	,238	9			
System	Entre grupos	,900	1	,900	4,500	,067
	Dentro de grupos	1,600	8	,200		
	Total	2,500	9			
Performance	Entre grupos	,400	1	,400	,571	,471
	Dentro de grupos	5,600	8	,700		
	Total	6,000	9			

FIGURE 5.9: ANOVA analysis between tasks of Brain Gain and Expressiveness Questionnaires - Cond.1

5.2.2 Condition 2

For condition 2 5.10, within expressiveness evaluation part, we can see that the mean value of the Brain Gain slight decreases between task 1 $(0,67)$ and task 2 $(0,51)$, 5.11. Nonetheless, we find no significance in these results $(p = 0,31)$, 5.12. We can also see an decrease valuation in System and Performance aspects between task, nonetheless, those are not significant $(p = 0,57)(p = 0,69)$, 5.12. Additionally, looking for correlations in all the measures, we can observe a positive correlation between system aspects and EEG arousal, where we observe a close to significant Pearson correlation ($rho = -0,73$,

$\sigma = 0,017$), 5.13.

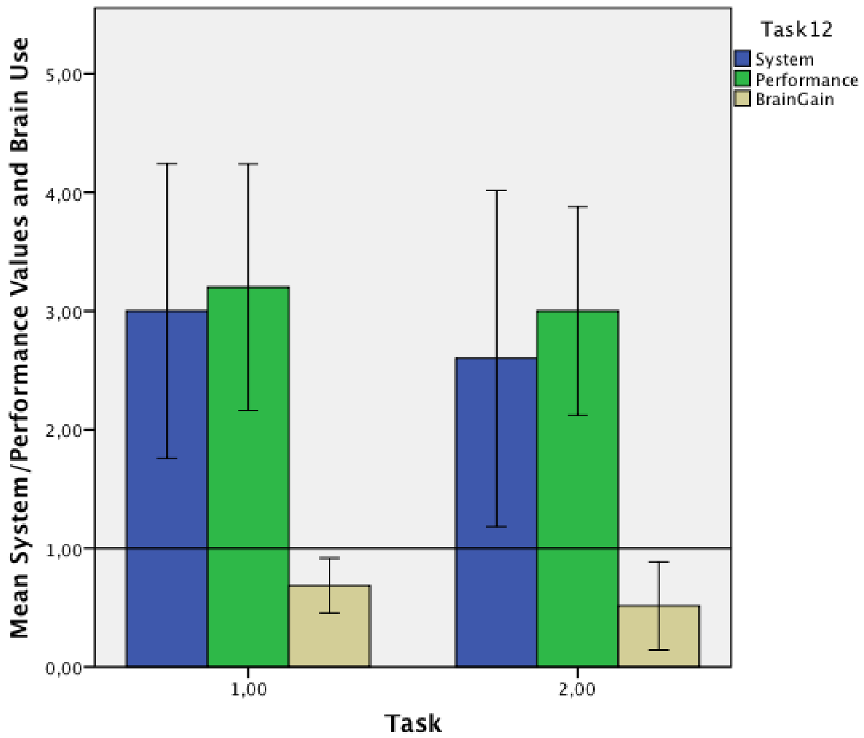

FIGURE 5.10: Mean Use of brain Gain and Likert Scale Ratings - Cond.2

Descriptivos

		N	Media	Desviación estándar	Error estándar	95% del intervalo de confianza para la media: Límite inferior	95% del intervalo de confianza para la media: Límite superior	Mínimo	Máximo
System	1,00	5	3,0000	1,00000	,44721	1,7583	4,2417	2,00	4,00
	2,00	5	2,6000	1,14018	,50990	1,1843	4,0157	1,00	4,00
	Total	10	2,8000	1,03280	,32660	2,0612	3,5388	1,00	4,00
Performance	1,00	5	3,2000	,83666	,37417	2,1611	4,2389	2,00	4,00
	2,00	5	3,0000	,70711	,31623	2,1220	3,8780	2,00	4,00
	Total	10	3,1000	,73786	,23333	2,5722	3,6278	2,00	4,00
BrainGain	1,00	5	,6860	,18596	,08316	,4551	,9169	,44	,88
	2,00	5	,5140	,29838	,13344	,1435	,8845	,11	,92
	Total	10	,6000	,25131	,07947	,4202	,7798	,11	,92

FIGURE 5.11: Descriptive Statistics of brain Gain and Likert Scale Ratings - Cond.2

ANOVA

		Suma de cuadrados	gl	Media cuadrática	F	Sig.
System	Entre grupos	,400	1	,400	,348	,572
	Dentro de grupos	9,200	8	1,150		
	Total	9,600	9			
Performance	Entre grupos	,100	1	,100	,167	,694
	Dentro de grupos	4,800	8	,600		
	Total	4,900	9			
BrainGain	Entre grupos	,074	1	,074	1,197	,306
	Dentro de grupos	,494	8	,062		
	Total	,568	9			

FIGURE 5.12: ANOVA of brain Gain and Likert Scale Ratings - Cond.2

Correlaciones

		ArousalEEG	ArousalSAm	ValenceEEG	ValenceSAM	System	Performance	BrainGain
ArousalEEG	Correlación de Pearson	1	,222	,367	-,033	,726*	,473	,061
	Sig. (bilateral)		,426	,178	,908	,017	,168	,867
	N	15	15	15	15	10	10	10
ArousalSAm	Correlación de Pearson	,222	1	-,016	,182	,318	,129	,474
	Sig. (bilateral)	,426		,955	,516	,371	,723	,166
	N	15	15	15	15	10	10	10
ValenceEEG	Correlación de Pearson	,367	-,016	1	-,450	,099	,117	-,249
	Sig. (bilateral)	,178	,955		,093	,786	,748	,489
	N	15	15	15	15	10	10	10
ValenceSAM	Correlación de Pearson	-,033	,182	-,450	1	-,431	-,345	-,139
	Sig. (bilateral)	,908	,516	,093		,214	,330	,702
	N	15	15	15	15	10	10	10
System	Correlación de Pearson	,726*	,318	,099	-,431	1	,467	,325
	Sig. (bilateral)	,017	,371	,786	,214		,174	,359
	N	10	10	10	10	10	10	10
Performance	Correlación de Pearson	,473	,129	,117	-,345	,467	1	-,048
	Sig. (bilateral)	,168	,723	,748	,330	,174		,895
	N	10	10	10	10	10	10	10
BrainGain	Correlación de Pearson	,061	,474	-,249	-,139	,325	-,048	1
	Sig. (bilateral)	,867	,166	,489	,702	,359	,895	
	N	10	10	10	10	10	10	10

Figure 5.13: Bivariate Pearson Correlation Analysis of Affective Responses and Expressiveness Measures - Cond.2

5.3 Open Questionnaires and Interviews Results

Here we present other questionnaire results regarding different aspects other than system or performance ones. Table below shows Likert Scale ratings from 1 to 5, where 1 means "strongly disagree" and 5 "completely agree". First item number 1 stands for global control condition, whereas second item 2 stands for local control condition.

- I loose control over music composition during performance:
  1. 3
  2. 3
- I liked musical timbre variations induced by the system.
  1. 3
  2. 3
- I enjoyed playing b-Reactable instrument.
  1. 4
  2. 3
- I would like to play with b-Reactable instrument in the future.
  1. 3

2. 3

- I think b-Reactable instrument fits well into a musical performance scenario.

    1. 2
    2. 3

Furthermore, we present some interesting points addressed by participants in an open interview after having performed last experiment.

- Subject ID 1:
    - *Global control has less control possibilities than local control, this one, is more natural and integrated in Reactable framework and is less restrictive.*
    - *I used both systems just if they were inputting a random signal. I didn't understand if there was a relation between my affective responses and system musical direction. I couldn't plan my performance based on BCI system.*
- Subject ID 2:
    - *I would like to have a mixed controlled system both local and global.*
    - *I felt the need of more sudden changes in music output when using brain objects.*
    - *It would be nice to have more brain lfo objects (local controllers) in order to apply them to different Reactable objects.*
- Subject ID 3:
    - *I didn't feel how the mapping was controlling music parameters yet I think it was design in the right way. I use signals as if they were random instead coming from my affective states.*
    - *This system could have sense in a neurofeedback training paradigm but non in a performance scenario, equipment is also so intrusive.*
- Subject ID 4:
    - *I didn't feel my affective state reflected in music tasks. I felt it was more random than it was showing a tendency. Maybe in local control the effect is less perceptive than in global control.*
    - *In global control, music events were happening in an unexpected way and in local control the effects were smooth because there was only one object to be controlled.*

  - *I would include a graphic mapping application in order to customise mapping. For instance, have a GUI where you can see your valence and arousal state and other GUI to change music parameters according to first GUI.*

- Subject ID 5:
  - *I only could feel smooth changes during both conditions. In that sense, I would like to change other music parameters like tonality with my valence and arousal.*
  - *I would implement more brain lfo's for the local control just to change more than one object at time.*

Chapter 6

Discussion

In this last chapter we will present an overall discussion of results that we show in chapter 4. First, we will discuss results from both conditions and from affective responses and music expressiveness measures. Later on, we will discuss the important differences between both conditions taking into account also the open interviews.

6.1 Global Brain Condition

From affective measures, even there is no significance difference in EEG levels between tasks (valence $p = 0,28$) (arousal $p = 0,612$), users affective responses change at a subjective level (valence $p = 0,071$) (arousal $p = 0,083$). Considering that both measures change in the same direction, we can say that there is an slightly moderate neurofeedback effect using the system.
From music expressiveness measures, we see that valuation on the system improves after tasks (close to significant, $p = 0,067$) due to a decrease use of the Brain Gain (correlated, $\rho = -0,783$, $\sigma = 0,007$). Nevertheless, there is no significance in the use of the Brain Gain and in performance aspects between tasks ($p = 0,471$). In that sense, we can not clearly affirm or deny that there has been an increase in music expressiveness using the system.

6.2 Local Brain Condition

From affective measures, there are no significance differences in EEG levels between tasks (valence $p = 0,49$) (arousal $p = 0,95$), and users affective responses change at a

subjective level only for the arousal (valence $p = 0,38$) (arousal $p = 0,049$). Taking into account that only arousal measures change in the same direction, we can not say that there is significant neuro-feedback effect using local control system.

Within expressiveness evaluation part, we can see that the mean value of the Brain Gain slight decreases between task 1 $(0,67)$ and task 2 $(0,51)$, yet, we find no significance in these results $(p = 0,31)$. We can also see a decrease valuation in System and Performance aspects between tasks, though, those are not significant $(p = 0,57)(p = 0,69)$. In addition, bi-variate analysis shows positive correlation between system aspects and EEG arousal $(\rho = 0,73,\sigma = 0,017)$. Summing all up, we can point out that (even there is no relevant significance) when the use of the brain gain is lower also the participants ratings on music expressiveness decrease.

6.3 Comparison Between Condition C1 and C2

There are no significant differences between C1 and C2 regarding both affective measures and music expressiveness ones $(p > 0,05)$. Nevertheless, we see a consistency between task direction and SAM subjective evaluations in both conditions, and similarly, consistency between arousal EEG measures and task direction. That could mean that the arousal classifier is more reliable than the valence one and more effort has to be applied to this last one.

In music expressiveness part, we see that system and performance aspects ratings are lower, both for C1 and C2, in high valence and high arousal tasks and are higher in low valence and low arousal tasks. This result may be explained by the fact that high valence and high arousal task need a major number of elements placed in the table. When this situation happens in a global control scenario it is easier to lose control over those objects. In a local control scenario for that task participants can loose the feeling of controlling the composition since they only have the possibility to change one object from the multiple ones placed in the table.

In addition, brain gain mean use is always above 50% in both conditions, so participants don't discard its function for composing their musical tasks. The fact that brain gain object mean use is always lower in task 2 than in task 1 can be explained by the occurrence when participants get use to it.

Summing all up, together with the open question interviews, we see that both systems have its pros an cons. From one hand, global control system is capable of augmenting the feeling that BCI signals are influencing in a wider range the overall music output. Tough, this can be diminishing performance control over composition. Local control system otherwise, has happened to be more customisable, and in this way it creates

a more accurate control when performing music tasks. Nevertheless, the music output effect it is not so noticeable since performer can only influence one object at time.

6.4 Future Work Directions

More experiments have to be carried out in order to assess the role of EEG physiology for the control of music systems in expressive ways. From one hand, this study has been rater focused on a particularly narrow group of Reactable expert users. Maybe, opening the system also to electronic music experts, and music experts in general, can lead us to wider results.
A between 3 conditions design can be done for this new target group in which it will have to perform a musical oriented task. The first condition will be with normal Reactable system, the second condition will perform with Reactable with the Global Controller and third condition will be with Reactable with Local Controller . The same user evaluation method like in Reactable Experts group will be carried out together with an analysis if they have reach or not the fixed musical target.

Moreover, an important point to be addressed is the use of robust and reliable affective responses classifiers, and specially for the valence one. This research domain into affective computing is quite new, and there is not a lot of literature a part from Koelstra et al.[2]. Other classification techniques have to be tested according to emotion databases in order to augment classification accuracy. A part from that, our Matlab script has to be cleaned up in order to increase calculation velocity and be able to send epocs in a time frame below 1 second. In that way, participants will be able to see a major influence, or at least a more continuum one, of BCI signals into the table.
As it has been pointed out in some interviews, creating a GUI to customise mappings will help to reinforce a perception link between users affective states and music features. Indeed, create a link between two tactile screen GUIs, one representing valence and arousal in a bidimensional space and other with the music parameters that can be manipulated. Moreover, it can be useful to create a kind of switch button, between local and global, in order to get best features from each of them.
The prime decision of only changing timbre parameters, with the manipulation of effects and filters, can be restructured in order to change other music parameters, such as tonality, loudness and tempo, which are more directly related to music emotions according to [3] and [19]. In this manner, the effect of BCI over music composition will tend to be more clear, despite it could lead to a lose of control over the composition.
Besides, other experimental designs that include external listener ratings on music expressiveness can be proposed. As well, musicians can rate their own music compositions

and try to point out interesting events happening in time. Correlating afterwards brain log measures with those events with a software platform like Repovizz [30], will probably tell us further useful information on music expressiveness.

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